Year: 2011

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DOI: https://doi.org/10.1109/PASSAT/SocialCom.2011.209

Originally published at:
Feese, Sebastian; Muaremi, Amir; Arnrich, Bert; Tröster, Gerhard; Meyer, Bertolt; Jonas, Klaus (2011). Discriminating individually considerate and authoritarian leaders by speech activity cues. In: Third IEEE International Conference on Social Computing: International Workshop on Social Behavioral Analysis and Behavioral Change (SBABC11), Boston, 9 October 2011 - 11 October 2011, 1-6.
DOI: https://doi.org/10.1109/PASSAT/SocialCom.2011.209

Discriminating Individually Considerate and Authoritarian Leaders by Speech Activity Cues

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***Abstract*—Effective leadership can increase team performance, however up to now the influence of specific micro-level behavioral patterns on team performance is unclear. At the same time, current behavior observation methods in social psychology mostly rely on manual video annotations that impede research. In our work, we follow a sensor-based approach to automatically extract speech activity cues to discriminate individualized considerate from authoritarian leadership. On a subset of 35 selected group discussions lead by leaders of different styles, we predict leadership style with 75.5% accuracy using logistic regression. We find that leadership style predictability is dependent on the relative discussion time and is highest for the middle parts of the discussions. Analysis of regression coefficients suggests that individually considerate leaders start speaking more often while others speak, use short utterances more often, change their speech loudness more and speak less than authoritarian leaders.**

I. Introduction

In today's business world, teams are a central aspect of organizational cooperation and their performance is crucial for organizational success [1]. It is widely accepted that effective leadership style can increase team performance. However, the influence of specific behavioral patterns of the team members on team performance is unclear. Recently, psychologists started to investigate how specific micro-level behaviors of team members like gestures or vocal expression influence the overall team performance. One major challenge when investigating behavioral patterns is that the available methods in psychology are still mostly based on manual annotation of video recordings and are thus labor intensive, time consuming, and prone to error due to subjective assessments.

A sensor-based, automatic acquisition and detection of nonverbal cues from body posture, gestures and vocal expressions could potentially discover such specific micro-level behaviors in an objective way and thus contribute to a better understanding of effective leadership style. Moreover, a sensor-based approach has the potential to measure micro-level behaviors outside the lab.

In this work, we describe our effort to characterize and classify two important leadership styles, *individualized consideration* and *authoritarian* leadership, with automatically extracted nonverbal cues from sensor data. We present an interdisciplinary laboratory study in which 165 participants completed a decision making task in groups of three under the guidance of a leader. Although group leaders were trained to show specific behaviors for each leadership style, not all leaders played their role perfectly, which motivated us to select a subset of discussions in which the leaders played their roles well. We describe our selection method and investigate how well speech activity cues differentiate leadership style. This work represents one step towards sensor-based discovery of micro-level behaviors of team leaders during meetings.

II. Prior and Related Work

A. Leadership Style in Social Psychology

Leadership has been examined from many perspectives and several leadership styles have been identified within the last century. In this paper we consider *individualized considerate* and *authoritarian leadership*. *Individual consideration* is a substantial facet of transformational leadership that has been found to increase team performance particularly well [2]. *Individually considerate* leaders pay special attention to their followers' needs and listen effectively [3]. As such, individual consideration is supposedly connected to "preference for and use of two-way communication, empathy, and willingness to use delegation" [3, page 132]. *Authoritarian* leaders on the other hand take decisions without consulting their followers [4]. Consequently, *authoritarian* leadership can only work as long as there is no need for input from the followers and their motivation does not depend on their involvement in the decision-making process. However, in the presented study, *authoritarian* leadership simply refers to the absence of *individual consideration*.

B. Social Computing

A review on the automatic analysis of social interactions in small groups can be found in [5]. Previous work in the social signal processing domain dealt with automatic inference of conversation structure [6], [7], [8], analysis of social attention [9], [10] and the detection of personality traits [11], [12] and roles [13], [14], [15]. These works mostly relied on speech related cues such as speaking length, speaker turns and number of successful interruptions. Additionally, physical activity cues were estimated with vision based methods, but only in few works motion sensors were used to track body motion. For classifying leadership style, the detection of dominance is especially important, because *authoritarian* leaders are more dominant than *individually considerate* leaders. On five minute slices extracted from 11 meetings of the AMI Meeting Corpus, dominance and status were automatically detected in [16]. For the dominance classification task, 59 meeting slices were manually annotated by three raters and two sets of either full or majority agreement among annotators were considered. Two classifiers were compared. An unsupervised approach simply classified the person with the smallest (highest) value of a cue, e.g. speaking time, as the most dominant person. This simple method was compared to Support Vector Machines for feature subsets. Accuracies ranged from 80% to 90% when classifying the most dominant out of four persons in a meeting. Nonverbal cues for predicting cohesion in small groups were investigated in [17]. From the AMI Corpus 120 segments of two minutes were annotated by external observers and segments with high inter-rater reliability were selected for the classification task of high and low cohesion. Nonverbal cues were compared by a simple threshold based classifier. More recently, correlations between emerging leadership in small groups with speech related nonverbal cues have been examined in [18]. A method to measure posture mirroring in social interaction was presented in [19] and results indicate that posture mirroring differs across groups of different leadership. In contrast to the works on meeting corpora, Pentland and collaborators investigated how wearable sensors can be employed to measure aspects of human behavior in daily life. Human behavior such as physical activity, speech activity and face-to-face interaction was recorded with sociometric badges to predict personality traits and group performance from sensor data [11].

III. Experiment

In order to investigate how micro-level behavior differentiates leadership styles, we conducted an experiment in which participants were discussing in groups of three persons under the guidance of a selected leader. Fifty-five groups were asked to work on a decision making task to rank four fictive candidates with regard to their suitability for an open job position. For the task, each group member received five pieces of information about each candidate that were partly shared among group members (hidden-profile decision making task). Under the guidance of the group leader, the group had to discuss the suitability of each candidate and agree on a rank order which served as a measure of group performance. The experiment design was proposed and first validated in [20].

A. Leadership Manipulation

As we are interested in behavior differences across leadership styles, leadership style was manipulated. Half of the leaders were instructed to show *individually considerate* leadership, whereas the other half was instructed to be *authoritarian*.

Upon arrival at the laboratory, the oldest group member was selected as the group leader and was led to a separate room where she received a short leadership training focusing

Fig. 1. Experiment setup: participants wearing sensor shirts.

either on *authoritarian* leadership or on *individually considerate* leadership. In five one-minute instruction videos typical behaviors of each leadership style were presented and the leader was asked to show these behaviors throughout the later discussion. As an incentive, leaders received a raffle ticket for a cash prize for each behavior that they displayed.

Leaders that were instructed to be *individually considerate* received the following instructions:

- Try to stimulate each of your followers to contribute his or her views and knowledge to the discussion
- Make sure that all of your employees contribute to the final decision
- Avoid pushing for your own opinion, e.g. after the group has arrived at a rank order ask each group member about any doubts regarding the decision
- Make suggestions on how the discussion might be structured and discuss these with your followers

In the control group, *authoritarian* leaders were instructed to show the following behaviors:

- Determine the structure of the discussion
- Be the first to suggest the rank order of candidates
- Interrupt unsuitable contributions of followers
- Decide on the optimal rank order of candidates after listening to the followers' opinions

B. Sensor Data Acquisition

Each group member was equipped with a separate clip-on lapel microphone. The speech of all group members was synchronously recorded at a sampling rate of 44.1 kHz via an USB-Audio-Interface on a PC. The upper body motion of each group member was captured with six inertial measurement units (IMU) (XSens MTx) which were located on both lower and upper arms, the back and the head (Fig. 1). Additionally, physiological data such as heart rate and breathing rate of each group member was recorded with a monitoring chest-belt (Zyphr BioHarness).

C. Video Annotation

All discussions were recorded on video and coded with the Discussion Coding System (DCS) [21]. The DCS is a state-of-the-art coding system to analyse group interaction. It dissects the group interaction into individual statements or acts of communication. Each act is transcribed in brief. Its accompanying interpersonal affect is coded on two dimensions: power (dominance vs. submissiveness) and affiliation (friendliness vs. hostility). The ratings on these dimensions are based on verbal and nonverbal cues as described in the DCS manual [21]. Examples include interrupting someone else or expressive gesticulation as markers for dominance. The function of a speech act is divided in main and minor categories. For the main category, it is coded whether the act is a social-emotional statement (differentiated in positive or negative), whether it is a statement with regard to the content of the task, or whether it is aimed at regulating the discussion. For each of these three main categories, the two minor categories proposal and question are coded, as these mark important process elements for decisions. Additionally, the reactions (agreement, rejection) following an act are coded.

D. Data Set

In total, we recorded data from 165 subjects (112 female, 53 male; age = 25.4 ± 4.2) in 55 group discussions. Due to a technical problem in one of the sensor shirts at the beginning of the experiment we lost sensor data of 11 subjects. In consequence, we ended up with a data set that includes 44 group discussions (16 groups were lead *authoritarian* and 18 with *individual consideration*) with three participants each. In the 44 selected sessions were eight male and ten female *individually considerate* leaders and five male and eleven female *authoritarian* leaders. Our data set totals to over 15 hours of discussion time.

IV. Methods

A. Check of Leadership Manipulation

After the discussion, the followers rated their team leader on the *individualized consideration* scale of the MLQ 5X leadership questionnaire [22]. *Individual considerate* leaders were evaluated as more individually considerate (M = 3.28, SD = 0.79) than in *authoritarian* leaders (M = 2.58, SD = 1.00, $t(108) = 4.13$, $p < .001$). Despite the statistical difference in the perceived *individualized consideration*, we noticed throughout the experiment that some of the group leaders did not lead their followers as instructed. This noise in the class labels decreases the performance of the leadership style classification task and motivated us to select a subset of discussions in which the leaders played their roles well. We therefore also check the leadership style manipulation with help of the video annotation. If we assume that the DCS captures relevant behaviors to differentiate leadership style and that only few leaders did not play their role well, we can calculate cues that summarize the leadership behavior of each group leader and use these for style prediction to exclude misclassified discussions. From the DCS, we calculated the following cues that summarize the behavior of the leader:

- *DCS Speaking Time* measures the relative speaking time in terms of discussion length
- *DCS Number of Questions Asked* asked by the leader divided by the total number of communication acts within the discussion
- *DCS Number of Proposals Made* made by the leader divided by the total number of communication acts within the discussion
- *DCS Affiliation* of each communication act was encoded on a five-point scale. We use the mean of all statements of the leader to measure affiliation of the leader towards the followers
- *DCS Power* of each communication act was encoded on a five-point scale and we use the mean of all statements of the leader to measure power of the leader towards his followers
- *DCS Number of Times Addressed* measures how often the leader was addressed by her followers normalized by the number of total communication acts per discussion

With these cues from the DCS, we fit a linear logistic regression model to predict leadership style. All discussions that are misclassified are excluded for the later analysis.

B. Speech Activity Cues

From the audio recordings we extract speech activity cues adopted from [16] to summarise the speaking behavior of each group member throughout the discussion. In a first step, relevant audio features such as signal energy were extracted for each frame (frame length: 25 ms, step size: 10 ms) with openSMILE [23]. Speaker diarization was performed by employing a simple threshold based approach. Speech for a group member was detected if the energy difference between the group members energy value and the mean value of the other group members was greater than an empirically set threshold. Speech activity segments shorter than 30 ms were then removed and segments of the same speaker within 1000 ms were merged. As in [16], [12] we follow a slice-based approach to calculate cues on discussion excerpts. We cut the discussion into non-overlapping slices of fixed length ranging from one minute to six minutes and calculate the following speech activity cues for each slice:

- *Average Single Speaking Energy (ASSE)* is the median of the signal energy per frame when a speaker speaks alone. The energy per frame is the sum of squared signal values multiplied by a hamming window.
- *Change Single Speaking Energy (CSSE)* is the inter-quartile range of the signal energy per frame when a speaker speaks alone.
- *Single Speaking Length (SSL)* measures the amount of time that a person speaks alone
- *Multiple Speaking Length (MSL)* measures the amount of time that a person speaks while at least one other person speaks
- *Total Speaking Length (TSL)* is the total amount of speech for each speaker; it is the sum of SSL and MSL
- *Speaking Turns (ST)* is the number of speaking turns for the person

- *Successful Interruptions (SI)* is the number of successful interruptions. Person i interrupts person j if person i starts talking while person j talks and person j stops before person i.
- *Unsuccessful Interruptions (UI)* is the number of unsuccessful interruptions. Person i does not interrupt person j if person i starts talking while person j talks and person i stops before person j.
- *Average Speaking Turn Duration (ASTD)* is the median turn duration
- *Change in Speaking Turn Duration (CSTD)* is the inter-quartile range of turn duration
- *Short Utterances (SU)* is the number of turns shorter than one second

To compare the slice based-approach, we also calculated the speech activity features for the whole length of each discussion and normalized them by the discussion length.

In addition to speech activity cues, we extracted prosodic features such as fundamental frequency, voice quality, voicing probability and formants. Prosodic features have been used in emotion recognition and capture how a person speaks and how much emphasis they give to a statement rather than how much a person speaks. We summarized the prosodic features over each slice by their median and inter-quartile range. However, we excluded all prosodic cues from further analysis because our data set contains an unequal distribution of males and female leaders (see III-D) and the fact that prosodic features also characterize gender. We tested the gender dependence of the prosodic features with the Wilcoxon rank-sum test. The test revealed that most of the cues were significantly dependent on gender and was the reason for us not to include prosodic features in the further analysis.

C. *Classification of Leadership Style from Speech Cues*

For the task of leadership style classification from automatically extracted speech cues we use logistic regression with the Lasso penalty term. We chose the logistic regression classifier because the Lasso shrinkage offers variable selection and the learned models can be easily understood by an analysis of the regression coefficients. As training data we take all slices from the leader and fit logistic regression models for each slice length. To obtain person independent results, we employ a leave-one-discussion-out cross-validation scheme and exclude in each fold all slices of one discussion as test data. From 35 available discussions we randomly sample 15 of each leadership style and calculate the cross-validated accuracy. We repeat this procedure 1000 times and report the mean and standard derivation of the accuracy. In addition to the slice-based accuracy, we use majority voting on the predictions of all slices of one discussion to predict which style the leader displayed in a particular discussion.

To investigate whether style prediction is dependent on the flow of the discussion, we calculate slices of fixed length at equally spaced intervals of the discussion. Considering different durations of the discussions, the start of each slice is relative to the discussion length. For each time step, we randomly sample 15 discussions of each leadership style to calculate the cross-validated accuracy. We report the mean and standard derivation for 100 sampling iterations.

V. Results and Discussion

A. *Check of Leadership Manipulation*

Classifying the leadership style using the cues from the DCS we achieve an accuracy of 79.2%. Nine of 44 discussions were not correctly classified and were excluded. Thus the selected subset contains 35 discussions out of which 17 were lead *authoritarian* and 18 with *individual consideration*. These discussions are 100% distinguishable with a linear logistic regression model and the cues from the DCS. The coefficients of the learned model are displayed in Figure 2. Analysing the coefficients, we notice that the most predictive variables are *DCS Number of Questions Asked* and *DCS Speaking Time*. This suggests that individually considerate leaders ask more questions and speak less than *authoritarian* leaders.

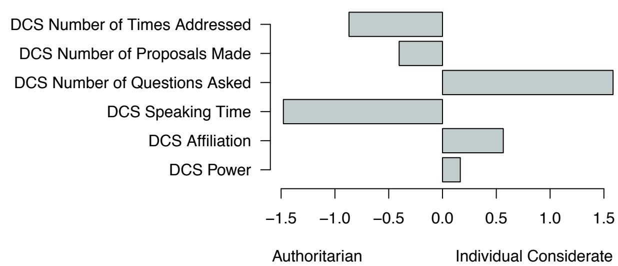

Fig. 2. Coefficients of the logistic regression model. Questions and speaking time are the most important variables to distinguish leadership style with variables of the discussion coding system.

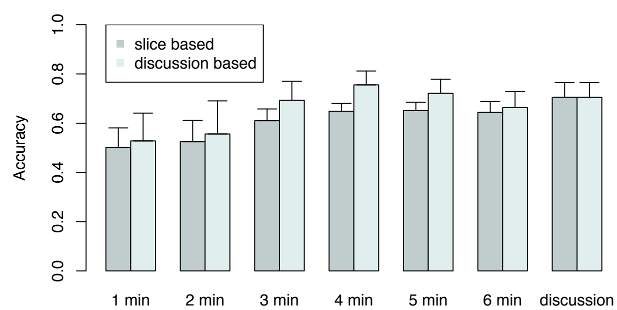

Fig. 3. Person independent performance of leadership style classification from speech activity cues. Mean and standard derivation of cross-validated accuracy.

B. *Leadership Style Detection from Speech Cues*

The results of the leadership style classification task for different slice lengths are presented in Fig. 3. The mean accuracy increases from slightly above chance level for one minute slices to 72.1% for five minute slices. The mean accuracy for slices over the entire discussion is 70.5%. Since one discussion consists of multiple slices, we can use the majority voting principle for the discussion based classification. For a discussion to be counted as correctly classified more than half of all slices of that particular discussion need to be correctly classified. The higher the slice based accuracy (for values above 50%) and the number of slices within a discussion, the higher is the discussion based accuracy. The optimal ratio for our one minute step analysis is reached at four minutes with an accuracy of 75.5%. Four minutes seems to be the shortest slice length in our data which captures enough speech activities needed for the extraction of meaningful speech cues to discriminate leadership style.

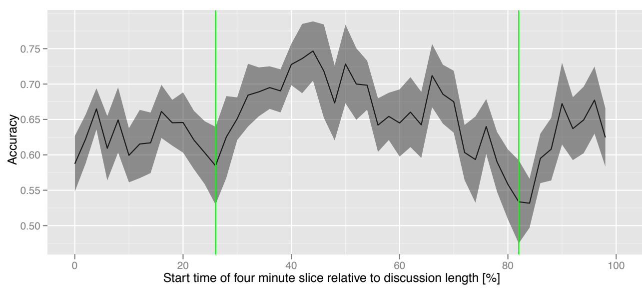

Fig. 4. Cross-validated leadership style classification accuracy (Mean and SD) over relative discussion time. Four minutes slices are shifted in time relative to the discussion length. Predictability of the leader is highest for the middle parts of the discussion.

Fig. 4 depicts the slice accuracy over the relative discussion time. The slice length is fixed to four minutes. It can be seen from the graph that the detection accuracy is low at the beginning and the end of the discussion and reaches its maximum in the middle of the discussion. From these observations, it can be stated that the ability to distinguish the leadership styles is dependent on the relative time of the discussion, and the best classification accuracy is achieved towards the middle of the discussion.

In order to better understand the importance of each speech cue, we analyse the coefficients of the fitted logistic regression models. A box plot summarizing the coefficients of the models trained on data of four minute slices is presented in Fig. 5. The most predictive variables are *Change in Single Speaking Energy*, *Speaking Time*, *Short Utterances* and *Interruptions*. Analysis of the coefficients reveals that *authoritarian* leaders speak more and have longer turns. This is coherent as these speech cues have also been found to be good predictors of dominance [16]. *Individually considerate* leaders instead, vary their speech loudness, have more short utterances and interrupt followers more often. These speech cues are linked to back-channeling and could indicate effective listening which is typical for *individually considerate* leaders [3, page 7].

VI. Conclusion and Outlook

We have presented a psychological experiment in which 165 subjects participated in groups of three under the guidance of a leader. Aiming at a better understanding of micro-level behavior of two different leadership styles (*individualized consideration* and *authoritarian*), we have used a subset of discussions for automatic prediction of leadership style. To select discussions in which leaders played their role as instructed, we have used a logistic regression model fitted on variables that summarize the leaders behavior as manually encoded by external observers. Using automatically extracted speech activity cues and a logistic regression, we detect the leadership style with an accuracy of 75.5%. Analysis of the regression coefficients shows that *individually considerate* leaders not only have shorter turns, but also use more short utterances and interrupt followers more often which taken together could signal effective listening and would be in line with the literature on leadership [3, page 7].

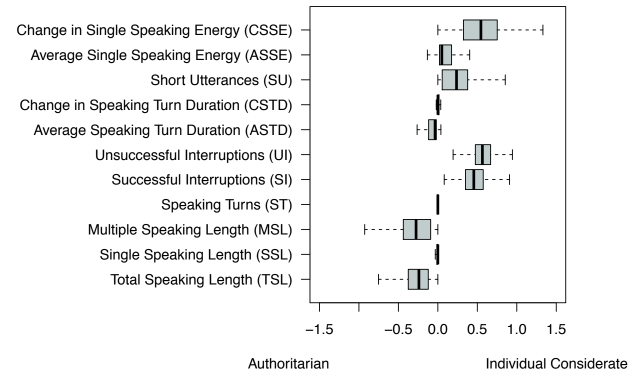

Fig. 5. Boxplot of regression coefficients for four minute slices. The coefficients suggest that *authoritarian* leaders speak more and have longer turns, whereas *individually considerate* leaders have more short utterances, vary their speech loudness and speak more often while followers speak.

In the present study we limited ourselves to speech cues from the leader. However, to better capture the discussion flow and conversational patterns, speech of all group members needs to be analysed. Future work will also include the analysis of body posture and gestures.

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